Whole-Brain Gray Matter Volume as an Anatomical Predisposition for Cognitive Ability

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Abstract

The human brain is the topic of much interest in recent years, and due to the advent and rising popularity of imaging techniques such as functional MRI, we are able to understand the brain with greater detail than ever before. Cognitive ability has always been known to be heavily tied to neuroanatomy, and existing research has shown that although cognitive skill is heavily dependent on specific brain regions such as the dorsolateral prefrontal cortex or hippocampus it is a highly delocalized function that involves the use of numerous brain regions. Larger volumes of whole-brain gray matter has also been shown to be tied to greater success on cognitive assessments implying that volumetric estimations of gray matter can serve as an indication of cognitive ability. Brain volume varies between individuals for a variety of reasons such as sex, age, ethnicity, and socioeconomic status. The former three of these are well understood biological principles or processes, but the last of these is a societal effect on physiology and may include diet and nutrition, education and social development, or occupation and family life. This paper will also examine whole-brain gray matter volumes in respect to education. Subjects (n = 60) were imaged to collect T1-weighted fMRI structural scans and were given Memory Assessment Scales examinations afterwards. We performed voxel-based morphometry using DARTEL in Statistical Parametric Mapping on the fMRI structural scans to acquire the volumes of gray matter, white matter, and cerebrospinal fluid of each individual. These gray matter volumes were then related to the individual's performance in a variety of cognitive domains tested for by the Memory Assessment Scales to examine if increasing gray matter volume has an

effect on the individual's performance. Years of education was also related to gray matter volume to observe if higher volumes correlated with higher education. Our findings suggest that gray matter does indeed demonstrate a small increase performance in some but not all cognitive domains tested for. The correlation with years of education pursued obtained was minimal, however it became slightly more pronounced in older individuals when the subjects were divided by age group. The brain volumes of the younger age group were determined to be statistically different from the older age group, but when these age groups were divided into high and low education classifications, the brain volumes from the two groups were not shown to be statistically different from each other. This indicates to us, that gray matter volume has a negligible effect on level of education pursued despite its seemingly positive effect on cognitive performance. It is important to understand that the mechanisms behind cognition are incredibly complex involving innumerable factors and that further exploration must begin at the biological level to expand our understanding of this phenomenon.

Acronyms and Initialisms:

fMRI - functional magnetic resonance imaging

SPM – Statistical Parametric Mapping

DARTEL – Diffeomorphic Anatomical Registration Through Exponentiated Lie Algebra

VBM – Voxel-Based Morphometry

DICOM – Digital Imaging and Communications in Medicine

NII / NIfTI – Neuroimaging Informatics Technology Initiative

GMV – Gray Matter Volume

WMV – White Matter Volume

CSF – Cerebrospinal Fluid

MNI – Montreal Neuroscience Institute

MAS – Memory Assessment Scales

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Introduction

Neuroscience has been the one of the great new frontiers of science beginning in the 20th century and new discoveries and advancements are made constantly that expand our understanding of the subject and the enigma of the inner of machinations of the brain. Cognitive ability and intelligence are an aspect of humanity that permeates into all functions of life. Despite how ubiquitous they are and the potential that discoveries in this field may have, there is still much to be investigated regarding the anatomical and physiological basis behind intelligence and cognitive ability.

Measuring intelligence requires accounting for three predominant variables behind individual cognitive performances. These include the specific test requirements, cognitive ability domains, and the testing of the general factor of intelligence or *g*-factor (Karama, S. et al., 2011). *G*-factor is a psychometric concept of quantifying intelligence by factor analysis of spatial-numeric reasoning. Criticisms have been made regarding measuring intelligence this way instead of categorically in different fields of intelligence such as word fluency, numeric ability, spatial ability and others. This criticism has been challenged by research that has shown that individuals that score well in one category of intelligence also tend to score well in others indicating the existence of some "*g*-factor" behind cognitive performance. Since the advent of *g*-factor and the further understanding of cognition, more methods of measuring cognitive ability such as the Montreal Cognitive Assessment or Memory Assessment Scales, have arisen all of which follow a central of theme of testing expertise in a variety of cognitive domains such as visual recognition or verbal span.

Previous research has found that brain volume is correlated ($r^2 = 0.33$) to higher values of g and overall cognitive performance. (McDaniel, M. A., 2005) This is reinforced by the realization that individuals with larger volume brains possess more tissue matter to create the complex synaptic circuitry required for higher order cognitive function. It is important to realize that larger volumes seem to only confer an advantage in creating the complex synaptic circuitry that goes behind cognition, and not an indication that a larger volume brain is necessarily indicative of higher cognitive function. Variations in brain and intracranial volume exist across sex, age, ethnicity, and aspects of socioeconomic status. Certain regions are particularly involved in cognitive ability. Regional neocortex thickness, particularly in the lateral prefrontal cortex has been shown to have profound impacts on the intelligence of individuals by consistently activating during a range of cognitive tasks. (Duncan J et al., 2000). Additionally, lesions in this region have been associated with loss of cognitive function. This does not imply that the LPFC is the seat of intelligence and cognitive ability in humans as it is a highly delocalized function that involves the synaptic activity of many brain regions, and for the purpose of this study we will be examining whole brain gray matter volumes, but it is important to recognize the importance of these specific regions.

The variations in brain volumes caused by the aging process has been researched extensively as well as the differences across the sexes. Brain volume changes profoundly across an individual's lifetime, particularly in early childhood and adolescence where male and female cranial capacities begin to diverge the most. (Lange, N., et al. 2010). However there has been markedly less research in the effects of ethnicity and socioeconomic status

on brain volume, the latter of which is particularly lacking investigation. The significance of socioeconomic status and its ability to create an environment that promotes a healthy, active, and constantly tested brain cannot be ignored. Using neuroimaging data across 60 individuals we will be examining the correlates of education to gray matter volume as determined through voxel-based morphometry from structural fMRI data. We use SPM12, a neuroimaging analysis software to examine the subject data. Using the DARTEL toolbox we are able to effectively carry out voxel-based morphometry to find the estimated total gray matter volumes of the subject brains (Ashburner, 2007)

There is an unfortunate reality that although progressive social ideologies have shifted to push for more equitable conditions for all, there still exists social inequities that provide advantages to some and obstacles to other. Socioeconomic status is one such injustice and one goal of this project is to investigate years of education pursued and its relation to gray matter volumes to possibly highlight education's effect on anatomical predisposition to cognitive ability.

Literature Review

Cognitive ability are aspects of life predicated on a variety of factors. The development of these brain functions is attributable to genetics, environmental conditions, and education. For cognitive ability to properly develop, it is essential that these needs are met within a critical window of an individual's childhood where they are most receptive to development. This window fluctuates between individuals, but it is unilaterally shown that early childhood is the most critical period for the development of the necessary synaptic circuits that underlie memory, learning, and cognitive function. This is due to a process called neural pruning, wherein the immature central nervous system creates an overabundance of neurons for the body to make use of, only to sieve out the extraneous neurons through adolescence and adulthood. This creates a "use it or lose it" dogma that reinforces the importance of facilitating conditions in early childhood to promote the development of cognitive abilities.

Above average cognitive skill has been shown to run in families, but this can be due to a genetic predisposition that is inherited across generations, or due to a sustained and enriching educational environment that is conducive to developing higher intelligence or most likely a combination of both. The role of genetics is often ignored because of how poor our understanding is of the numerous genes that contribute to cognition. Recently however, more genes are being shown to facilitate or hinder cognitive development, such as the apoliprotien E gene, e4 that is heavily involved in Alzheimer's risk, and has been shown to also promote the rapid degradation of hippocampal tissue in late adulthood

(Cohen et al., 2001). Previous research on the genetic predispositions for cognitive abilities has indicated that a multitude of brain regions play a role in the manifestation of cognitive abilities but there are key areas that have been shown to play an essential part. One of these regions is the pre-frontal cortex, one of the most evolutionarily novel cortical regions. The dorsolateral prefrontal cortex (DLPFC) holds executive power over the operations of the other brain regions and is associated with many functions involving memory, emotions, and perception. Another region of great interest is the hippocampus, a subcortical region of the limbic system which is regarded as the seat of long-term memory and vital in the acquisition and consolidation of semantic and episodic memories. This affords it a significant role in the learning process as was demonstrated by Patient H.M. whose impaired entorhinal cortex, the pathway of information to the hippocampus, eliminated his ability to create new memories. (Squire, 2011)

Despite the knowledge that these regions are of key importance, the manifestation of cognitive abilities utilizes and integrates so many regions that it is impossible to name an anatomical seat of cognition. This widespread distribution has allowed raw measurements of the entire cortical volume to be compared to tested cognitive ability by a variety of scientists and their findings indicate that larger brains are usually indicative of higher intelligences (McDaniel, M. A., 2005), and particularly with higher thicknesses in the neocortex (Shaw, P., 2007). There are discrepancies between individuals across sex, age, ethnicity, socioeconomic status (Rushton and Ankney, 1996, Rushton, 1997). Male cranial cavities are typically larger than female cranial cavities although there is evidence to show that this does not produce an appreciable difference in cognitive ability between sexes,

indicating that sex-specific processes are at work that mitigate these anatomical discrepancies (Gur et al., 1999). Older individuals also have smaller brain volumes compared to younger adults due in larger part to natural deterioration, but also possibly due to neurodegenerative diseases (Chee et al., 2011). However, there exists a smaller amount of research exploring discrepancies in brain volumes across ethnicities and socioeconomic statuses, particularly the latter of these. Socioeconomic status is significantly more difficult to truly gauge on an objective scale as it entails the qualities of one's environment. The differences observed in individuals at different tiers of socioeconomic wellbeing can be attributed to minute biological differences across people, specific cultural attitudes towards parenting and upbringing, and monetary inequities of early childhood nutrition and development, and education quality throughout life.

There exist some logistical difficulties in this study, but these can be addressed also by examining the methods employed by previous researchers. Estimating brain volumes requires the complex process of voxel-based morphometry which entails volumetric analysis in an analysis software. (Siddiqi et al., 2011).

Methodology

There are three specific sets of data we are endeavoring to acquire in this study. The first of these is gray matter volume estimations produced by voxel-based morphometry of T1-weighted fMRI structural imaging data. Over the course of the past several years our lab has conducted several studies involving fMRI brain images of local volunteers. These images were saved onto a private database where they were retrieved for the purpose of this study. As part of the scanning procedure, an initial T1-weighted structural scan was taken to image the gross anatomy of the individual's brain. Using Statistical Parametric Mapping software, we can use voxel-based morphometry to calculate the whole-brain gray matter volume. Due to the timeline of the study and to keep all available data consistent, data for 60 participants used for the same previous study were used for this procedure with 28 older adults age 65 and above and 32 younger adults ages 18 to 35. In addition to the fMRI scanning procedure, each of the participants' demographical information was documented with a particular emphasis on pivotal points of brain volume variance: age, sex, ethnicity, and education. The reported years of education would be used in relation to the subject's gray matter volume. They were also given an assessment that quantified their cognitive ability as a numeric score in a variety of cognitive domains using an industry-standard neuropsychological exam called the Memory Assessment Scales. The gray matter volumetric data was cross-referenced with the subject's years of education as well as cognitive assessment performance to see if the existing knowledge of larger whole-brain

gray matter volumes indicating higher cognitive abilities is consistent with our own data and if that same phenomenon manifests in the years of education an individual pursues.

The analysis of the fMRI images required the use of SPM12, a MATLAB based statistical software that is used for the analysis of brain images. However, this software is ill-quipped to carry out voxel-based morphometry due to its inability to model detailed deformations. This called for the use of a toolbox known as Diffeomorphic Anatomical Registrations through Exponentiated Lie Algebra or DARTEL for short. This extension to SPM12 provides the tools and templates to carry out accurate inter-subject registration of images (Ashburner, 2007). The 60 T1-weighted structural scans, initially existed as approximately 176 individual DICOM files. They needed to be imported into SPM12 as NIfTI (nii) file types to progress with the analysis and so the DICOM importer in SPM was used Initially reoriented in three-dimensional space to fit the canonical template which required manually adjusting the X, Y, and Z-axes so that the templates matched. This is good practice to ensure that that the segmentation phase is accurate. It is imperative that any and all readjustments be linear or affine transformations. Non-linear transformations can impair the data for normalizations and misconstrue actual volumes (Bogdanov, 2017)

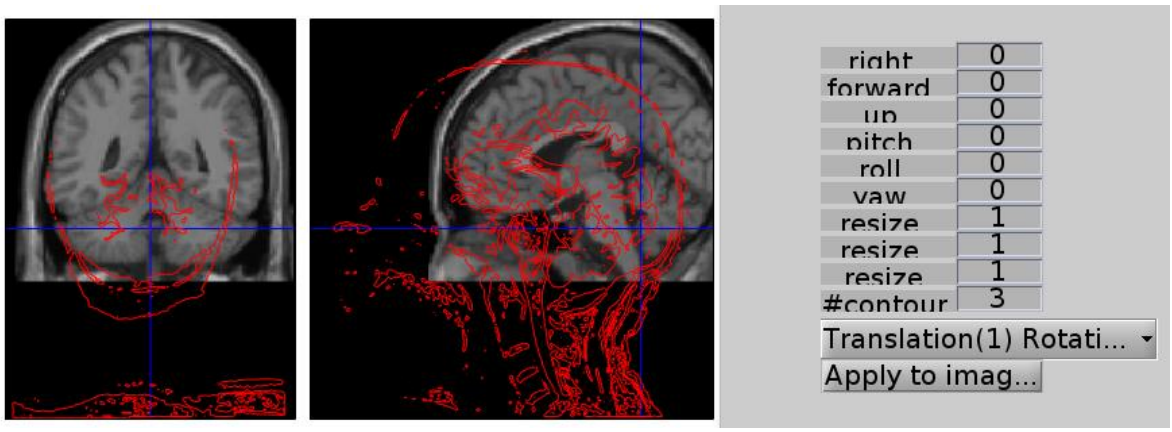

Figure 1- Manual Readjustment of T1-Weighted Structural Scans with Respect to SPM Canonical Image.
Each individual's structural image needed to be manually reoriented by linear transformations to match the canonical image in order to avoid errors during segmentation.

After these adjustments are made to match the canonical image, the next step of the process was to undergo segmentation which would take the T1-Weighted structural scans and divorce six tissue classifications as separate NIfTI image files. The first and second of these segmentations are gray matter (c1) and white matter (c2). The other four are cerebrospinal fluid (c3), skull bone (c4), soft tissue (c5) and air (c6). In addition to these segmentations are two additional NIfTI files, the rc1 and rc2 files which also depict the gray and white matter segmentations after spatial normalization. These files will be of use for the next step. Also a seg8.mat file was create that can be used for early estimation of tissue volumes.

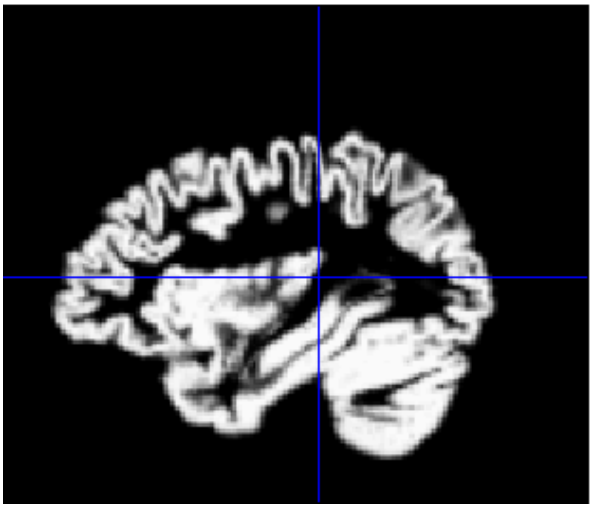

Figure 2 - Gray Matter Segmentation

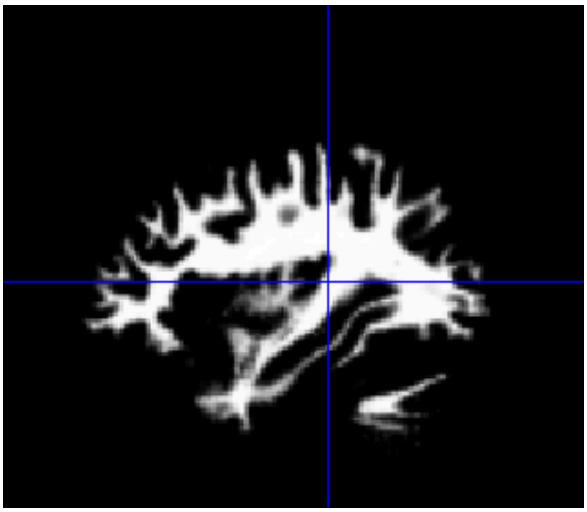

Figure 3 - White Matter Segmentation

The next step was to run DARTEL and create templates using each subjects' generated rc1.nii gray matter and rc2.nii white matter files in order by flow field. DARTEL is able to enable accurate inter-subject registration by using three parameters per voxel to shape each brain therefore having parameters numbering in the millions instead of the

thousands used outside of DARTEL (Ashburner, 2007). Six iterations of conglomerate templates were created from the subject data and an "u_rc1" file encoding shapes was made for each subject.

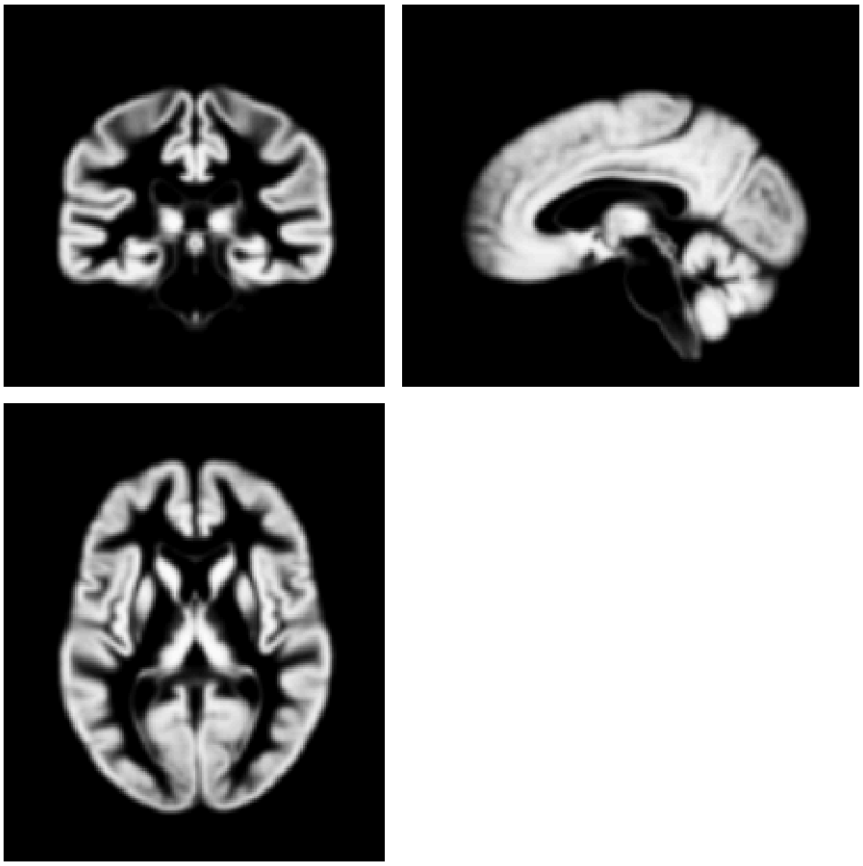

Figure 4 – Template 6 Image
Coronal, Sagittal, and Axial View of Sixth Iteration Template of Subject Data generated by Run DARTEL (Create Templates) Module

The next phase is to normalize the resulting "u_rc1" images into MNI space. Using the sixth iteration template created by the previous step and using the c1.nii and rc1.nii files produced in the segmentation phase all the brains are normalized to warp images aligning

with the average-shaped template using affine registration of the template and smoothing such that there is minimal signal loss. The process produced a “smwc1.nii” file for each subject.

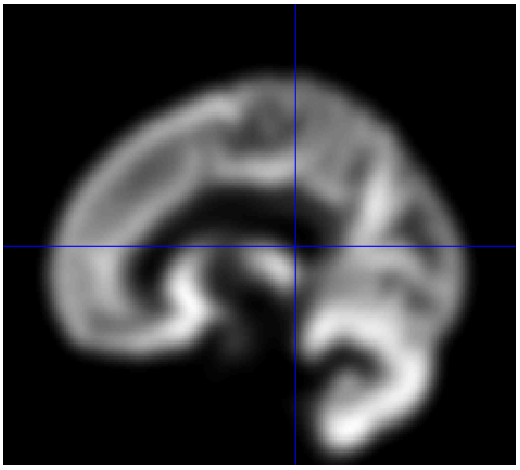

Figure 5 - Gray Matter Image after Normalization to MNI Space and Smoothing

Finally we are able to run the Tissue Volume module that takes the seg8.mat files generated previously to output the volume in liters of various tissue classifications. For the purpose of this study, we are not interested in bone, soft tissue, nor air volumes so the maximum tissue class was set to 3 for gray matter, white matter, and CSF. The latter two were calculated to have an indication of total intracranial volume for later use. We now have our subject gray matter volume data ready for comparison with Memory Assessment Scales scores and years of education pursued. T-tests were performed on each cognitive domain tested for in the memory assessment scales as well as the subject’s years of education pursued to determine significance.

Results

	GMV	WMV	CSF	TIV
n	60	60	60	60
mean	0.675355	0.435367	0.295125	1.405847
median	0.6589	0.4265	0.2543	1.4057
standard deviation	0.100203	0.05491	0.101683	0.130138
variance	0.010041	0.003015	0.01034	0.016936

Table 1 – Descriptive Statistics of Volumetric Data
Depicts sample size, arithmetic mean, median, standard deviation and variance. All volumes are expressed in liters (L).

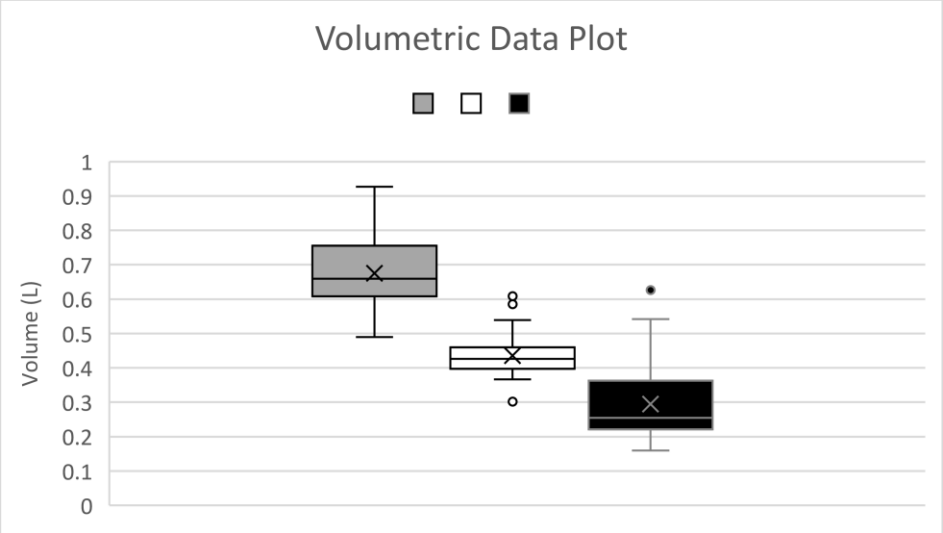

Figure 6- Volumetric Data Plots
Depicts box-and-whisker plots of the calculated gray matter, white matter, and cerebrospinal fluid showing the mean, median, interquartile range, maximum, minimum, and calculated outliers.

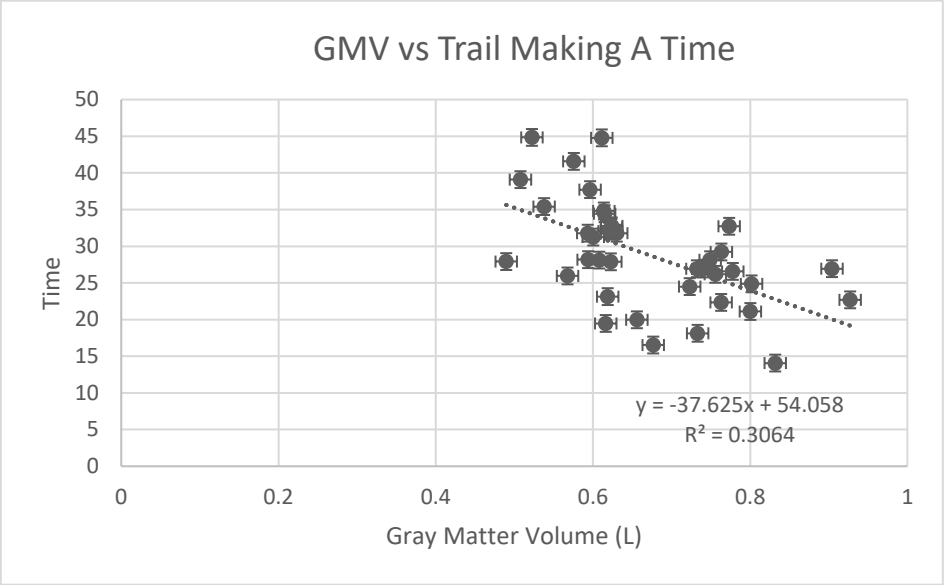

Figure 7 - Gray Matter Volume vs Trail Making A Time
Gray Matter Volume plotted with the time taken by the individual to complete Trails A, a pattern recognition task in the Memory Assessment Scales. A linear regression line made via least squares method and coefficient of determination of ~ 0.3064

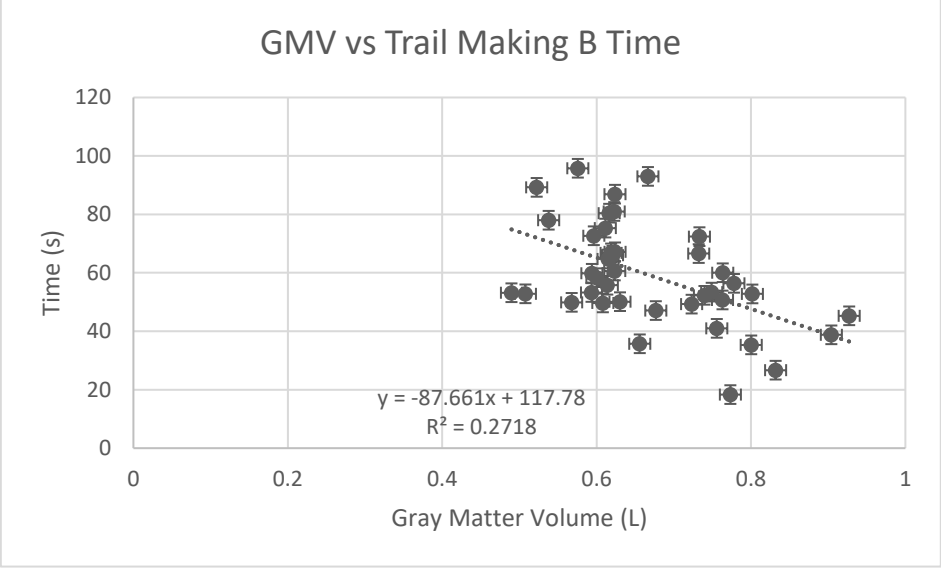

Figure 8 - Gray Matter Volume vs Trail Making B Time
Gray Matter Volume plotted with the time taken by the individual to complete Trails B, a pattern recognition task in the Memory Assessment Scales. A linear regression line method and coefficient of determination of ~ 0.2718 are included.

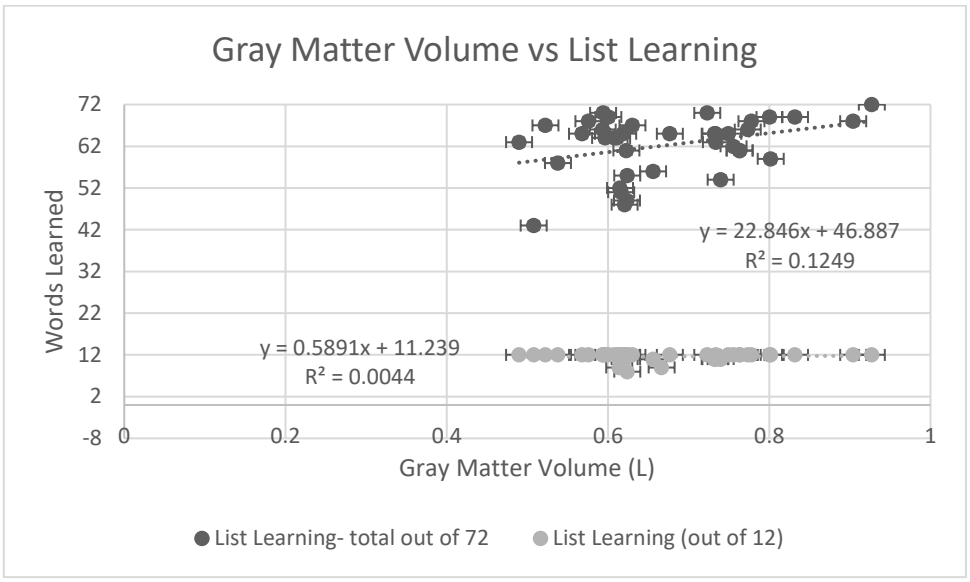

Figure 9 - Gray Matter Volume vs List Learning
Gray Matter Volume plotted with number of words learned from a list of 72 and a list of 12, in the Memory Assessment Scales. A linear regression line and coefficient of determination of ~ 0.1249 for Total Learning of 72 and ~0.0044 for Out of 12 are included.

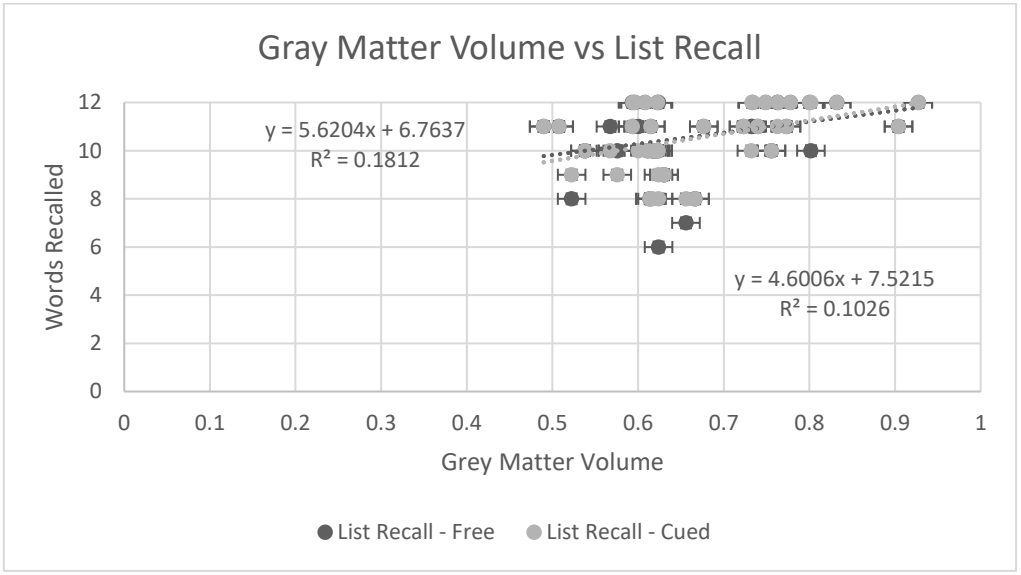

Figure 10 - Gray Matter Volume vs List Recall
Gray Matter Volume plotted with the number of words recalled from a list of 12 words in the Memory Assessment Scales. Linear regression lines and coefficient of determination of ~ 0.1812 for free recall and ~0.1026 for cued recall are included.

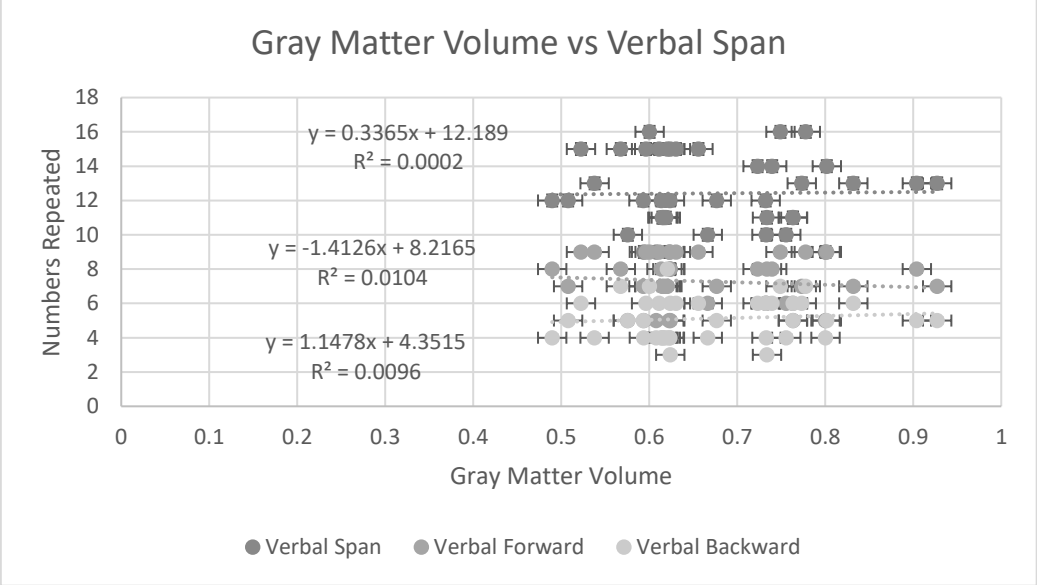

Figure 11- Gray Matter Volume vs Verbal Span
Gray Matter Volume plotted with the sum quantity of number sequences repeated forwards and backwards in the Memory Assessment Scales. Linear regression lines and coefficient of determination of ~ 0.002 for Verbal Span, ~0.0104 for Verbal Forward, and ~0.0096 for Verbal Backward are included.

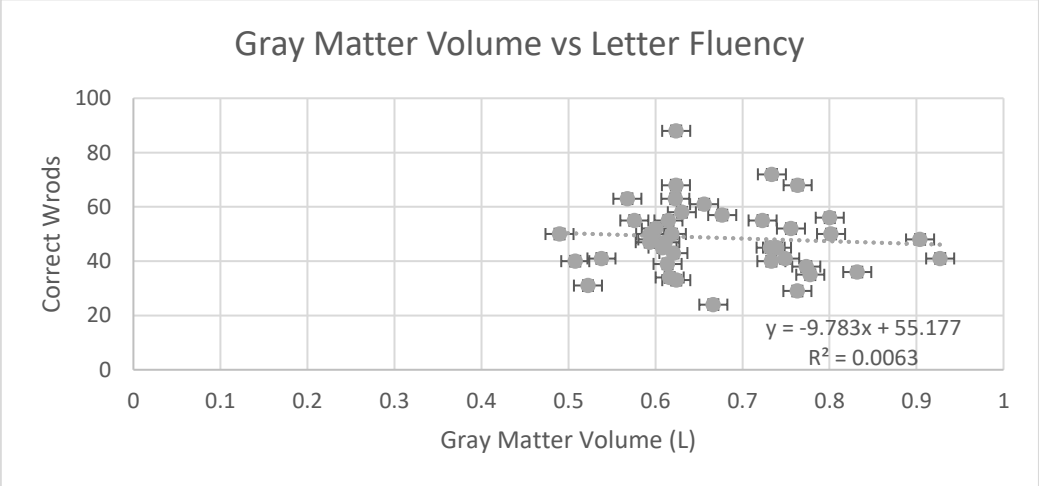

Figure 12- Gray Matter Volume vs Letter Fluency
Gray Matter Volume plotted with the number of words the subject was able to come up with that began with a cued letter in the Memory Assessment Scales. Linear regression lines and coefficient of determination of ~ 0.0063

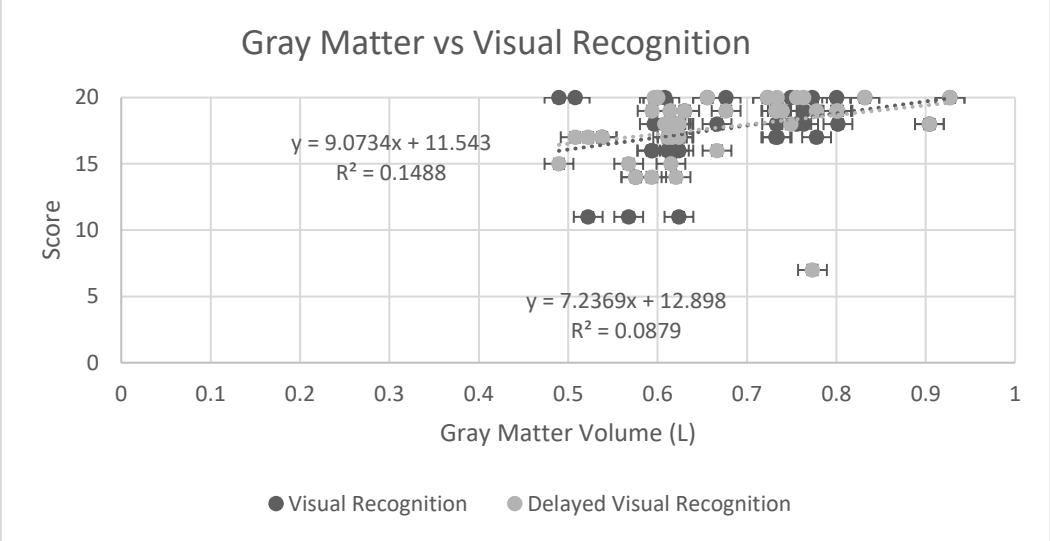

Figure 13- Gray Matter Volume vs Visual Reproduction
Gray Matter Volume plotted with score from the Memory Assessment Scales. Max score was 20. Linear regression lines and coefficient of determination of ~0.1488 for visual recognition and ~0.0879 for delayed visual recognition are included.

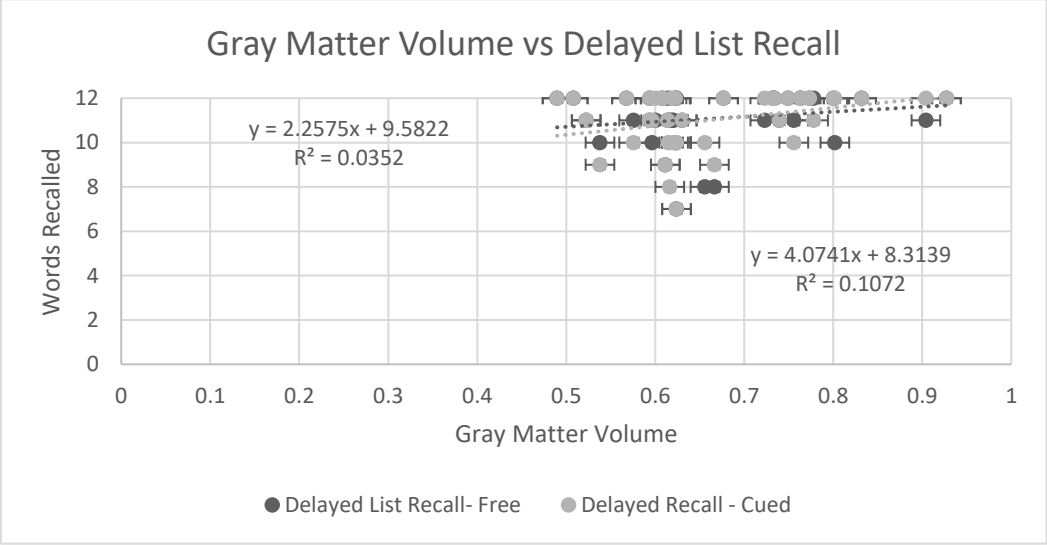

Figure 14- Gray Matter Volume vs Delayed List Recall
Gray Matter Volume plotted with the number of words recalled from a list of 12 words after a delay in the Memory Assessment Scales. Linear regression lines and coefficient of determination of ~ 0.0352 for free recall and ~0.1072 for cued recall are included.

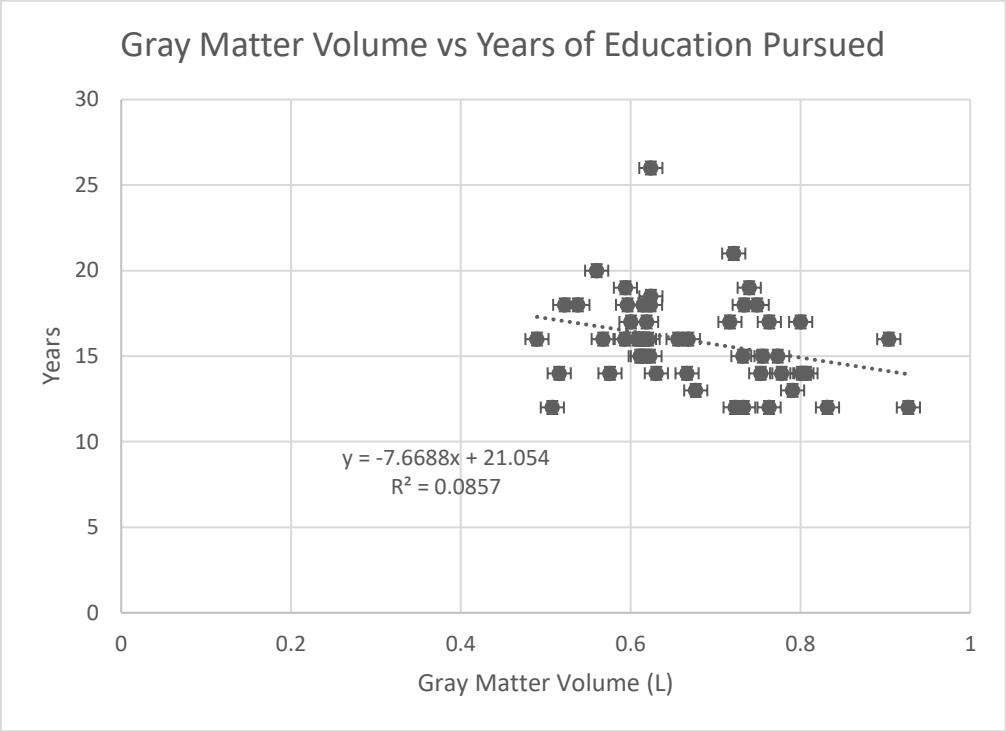

Figure 15- Gray Matter Volume vs Years of Education Pursued
Gray Matter Volume plotted with the years of education the individual pursued. A linear regression line and coefficient of determination of 0.0857 are included.

	Total Age	Total Education
Mean	42.31481	15.69444
Median	29	16
Standard Deviation	23.04571	2.660438
Variance	531.1046	7.077932

Table 2 – Age and Education Descriptive Statistics
Depicts arithmetic mean, median, standard deviation and variance of all subjects' age and education. All durations are expressed in years.

	OA Age	OA Education	OA GMV
Mean	67.5	16.72916667	0.589596
Median	69	16	0.6004
Standard Deviation	4.734624237	2.665282844	0.047899
Variance	22.41666667	7.103732639	0.002294

Table 3 – Age, Education, and GMV of Older Adults Descriptive Statistics
Depicts arithmetic mean, median, standard deviation and variance of older adult (65+) age, education, and GMV. All durations are expressed in years, and all volumes are expressed in liters (L)

	YA Age	YA Education	YA GMW
Mean	22.16666667	14.86666667	0.74682
Median	21	14.5	0.7512
Standard Deviation	4.967114074	2.348521994	0.072525
Variance	24.67222222	5.515555556	0.00526

Table 4 - Age, Education, and GMV of Younger Adults Descriptive Statistics
Depicts arithmetic mean, median, standard deviation and variance of younger adult (18-35) age, education, and GMV. All durations are expressed in years, and all volumes are expressed in liters (L)

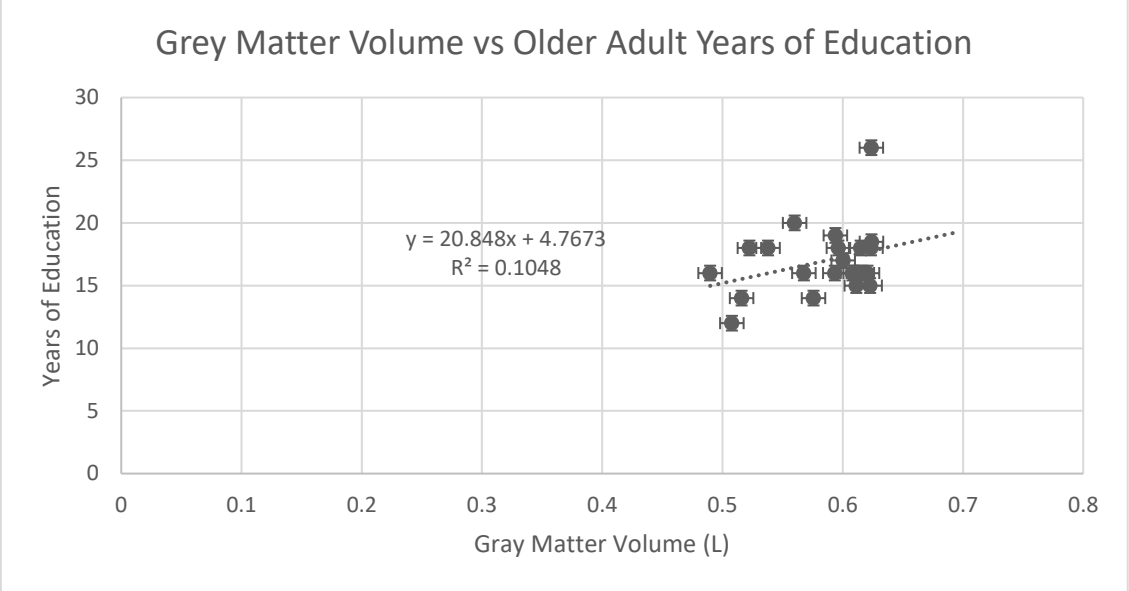

Figure 16 - Gray Matter Volume vs Years of Education Pursued by Older Adults
Gray Matter Volume plotted with the years of education the individual pursued. A linear regression line and coefficient of determination of 0.1048 are included.

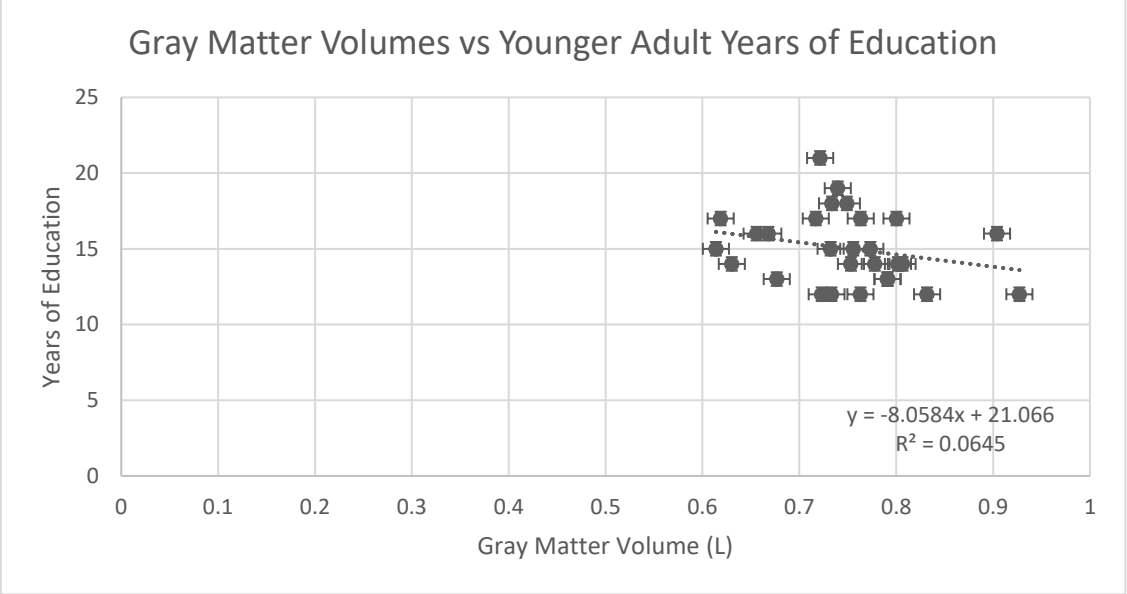

Figure 17 - Gray Matter Volume vs Years of Education Pursued by Older Adults
Gray Matter Volume plotted with the years of education the individual pursued. A linear regression line and coefficient of determination of 0.0645 are included.

Table 5 - Independent t-Tests at 95% Confidence Interval

Trails A							
	Mean	SD	SEM	N	df	t	**p**
Above Average GMV	25.0388	5.7714	1.3998	17	39	3.596	**0.0009**
Below Average GMV	32.6896	7.2944	1.489	24			**Significant**
Trails B							
	Mean	SD	SEM	N	df	t	**p**
Above Average GMV	66.5183	15.7738	3.2198	17	39	3.8189	**0.0005**
Below Average GMV	48.46	13.5904	3.2961	24			**Significant**
Free List Recall							
	Mean	SD	SEM	N	df	t	**p**
Above Average GMV	11.35	0.7	0.17	17	39	2.9535	**0.0053**
Below Average GMV	10.08	1.67	0.34	24			**Significant**
Cued List Recall							
	Mean	SD	SEM	N	df	t	**p**
Above Average GMV	11.41	0.71	0.17	17	39	4.0864	**0.0002**
Below Average GMV	9.92	1.38	0.28	24			**Significant**
Verbal Span							
	Mean	SD	SEM	N	df	t	**p**
Above Average GMV	12.47	2	0.49	17	39	0.1319	**0.8958**
Below Average GMV	12.38	2.46	0.5	24			**Not Sig**
List Learning (of 72)							
	Mean	SD	SEM	N	df	t	**p**
Above Average GMV	64.82	4.52	1.1	17	39	2.1376	**0.0394**
Below Average GMV	60.24	7.84	1.71	24			**Significant**
List Learning (of 12)							
	Mean	SD	SEM	N	df	t	**p**
Above Average GMV	11.82	0.39	0.1	17	39	1.1185	**0.2702**
Below Average GMV	11.5	1.14	0.23	24			**Not Sig**

Letter Fluency

	Mean	SD	SEM	N	df	t	**p**
Above Average GMV	47.53	11.57	2.81	17	39	0.4525	**0.6534**
Below Average GMV	49.38	13.7	2.8	24			**Not sig**

Visual Recognition

	Mean	SD	SEM	N	df	t	**p**
Above Average GMV	9.24	1.03	0.25	17	39	5.9769	**0.0001**
Below Average GMV	5.58	2.36	0.48	24			**Significant**

Delayed Visual Recognition

	Mean	SD	SEM	N	df	t	**p**
Above Average GMV	18.59	3.06	0.74	17	39	1.8329	**0.0745**
Below Average GMV	17.17	1.9	0.39	24			**Not Sig**

Delayed List Recall Free

	Mean	SD	SEM	N	df	t	**p**
Above Average GMV	11.65	0.61	0.15	17	39	2.544	**0.015**
Below Average GMV	10.71	1.43	0.29	24			**Significant**

Delayed List Recall Cued

	Mean	SD	SEM	N	df	t	**p**
Above Average GMV	11.76	0.56	0.14	17	39	3.3733	**0.0017**
Below Average GMV	10.54	1.41	0.2	24			**Significant**

Gray Matter Volume

	Mean	SD	SEM	N	df	t	**p**
Younger Adults	15.036	2.365	0.447	17	39	2.6184	**0.0118**
Older Adults	16.932	2.753	0.58	24			**Significant**

Gray Matter Volume

	Mean	SD	SEM	N	df	t	**p**
Higher Education	0.652261	0.08386	0.019766	18	48	1.2148	**0.2304**
Lower Education	0.689066	0.111872	0.019776	32			**Not sig**

Discussion

The results of this study indicates to us that whole-brain gray matter volume does indeed have an impact on the cognitive performance of an individual. We expected to observe higher gray matter volume individuals to demonstrate greater success in cognitive tasks. This hypothesis was in large part supported by the data with several of the tasks delineated in the Memory Assessment Scales showed stronger performances in line with increasing gray matter volume. The specific data that in support of this expectation were in Trails A time ($r = -0.55$), Trails B time ($r = -0.52$), Free and Cued List Recall ($r = 0.43$, $r = 0.32$), List Learning of 72 Words ($r = 0.35$), Immediate Visual Recognition ($r = 0.39$), and Delayed Free and Cued List Recall ($r = 0.19$, $r = 0.33$) all of which correlated with gray matter volume with significance ($p < 0.05$).

Significance was determined via two-tailed two-sample unpaired t-tests of the subjects divided into those with GMVs above and below 0.6752 L after performing a Kolmogorov-Smirnov Test of Normality ($D = 0.15$) to ensure the gray matter volume data was distributed normally. Those with below average GMV values and those with above average GMV values were referred to as such and the MAS scores attached to the individuals of each group were used as the sample for the t-test.

An important distinction to note is that although several of the MAS tested cognitive tasks showed significant correlation with gray matter volume, there were exceptions. Those included Verbal Span and therefore Verbal Forward and Verbal Backward, List Learning of 12 words, Delayed Visual Recognition, and Letter Fluency. It

is unclear if there is anything particular about these cognitive domains that would explain the lack of correlation with gray matter volume, but once again it is important to remember that cognition is a complex process utilizing numerous regions of the brain in different capacities and we are ill-equipped to control for every possible event.

In order to demonstrate gray matter volume changes with age, a two-sample two-tailed, unpaired t-test was conducted on the gray matter volumes of younger adults (18-35) and older adults (65+). The results showed significant difference between the two samples, highlighting the effect of aging on whole-brain gray matter volumes.

Education was another point of interest in regards to its relationship with whole-brain gray matter volumes. It was initially expected that individuals with higher gray matter volumes would also demonstrate greater years of education pursued. The subjects were divided into groups of those that have completed over the median 16 years of education and/or reported acquisition of a 4-year degree, who were classified as higher education individuals, and those with fewer years of education than the median were classified as lower education individuals. After this division was made a two-sample two-tailed, unpaired t-test was conducted on the gray matter volumes of each educational classification. The result showed no significant difference between the two samples contrary to our expectations. Although the reason for this discrepancy cannot be definitively determined the population sampled from may have played a role in affecting the data. The older adults showed closer correlation to gray matter volume than the younger adults likely in large part due to the diverse array of educational backgrounds in the older

adult subjects. Younger adults were almost exclusively students attending university where they were actively exercising and challenging their brains with consistent stimulating experiences. A greater diversity of educational backgrounds could perhaps alleviate this effect and isolate an effect of gray matter volume on the pursuit of education.

Conclusions

So in conclusion we found that whole-brain gray matter volume does seem to act as an anatomical predisposition to cognitive ability. We accomplished this by taking existing 60 subjects' T1-weighted fMRI images and using them for voxel-based morphometry. After realigning, segmentation, DARTEL, and normalization we obtained tissue volumes for whole brain gray matter, white matter, and CSF. The subject's years of education and Memory Assessment Scales scores were used for further analysis. Although there seems to be a demonstrable effect of higher GMVs, this effect may be limited to specific domains of cognition and not an outright unconditional fact. This was demonstrated by the fact that despite several of the cognitive domains tested in the Memory Assessment Scales correlating significantly with the volumes, some domains did not. We also found that whole-brain gray matter volume does not indicate the years of education an individual will pursue with no significant difference between those of lower and higher education designations. The reasons for this are unclear, and it is still possible gray matter can play a role in education. Cognition is a complex poorly understood process with so many factors involved in its manifestation that it is currently impractical to expect to be able to control for everything. Future work in this area should aim to increase the sample size for more generalizable data with more statistical power. The samples should be taken from a greater diversity of individuals with cognizance of the key points of brain anatomy variance: age, sex, ethnicity, and socioeconomic status. The importance of expanding our understanding of cognition cannot be understated. Our knowledge on this fascinatingly multifaceted

process begins in its biological foundations as we explore the anatomy and physiology behind cognition.

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